5-2-2007

Neuroeconomic Studies of Impulsivity: Now or Just as Soon as Possible?

Paul W. Glimcher
New York University

Joseph W. Kable
University of Pennsylvania, kable@psych.upenn.edu

Kenway Louie
New York University

Recommended Citation

Glimcher, P. W., Kable, J. W., & Louie, K. (2007). Neuroeconomic Studies of Impulsivity: Now or Just as Soon as Possible?. *American Economic Review,* 97 (2), 142-147. http://dx.doi.org/10.1257/aer.97.2.142

Neuroeconomic Studies of Impulsivity: Now or Just as Soon as Possible?

Abstract
Existing behavioral studies of intertemporal choice suggest that both human and animal choosers are impulsive. One possible explanation for this is that they discount future gains in a hyperbolic or quasi-hyperbolic fashion (David I. Laibson 1997; Shane Frederick, George Loewenstein, and Ted O'Donoghue 2002). This observation stands in contrast to standard normative theory, which predicts exponential discounting for any single maximizing agent (Robert H. Strotz 1956). This disparity between empirical and normative approaches is typically explained by proposing that human choosers suffer from inner conflict, balancing an impulse for an immediate gratification against other forces calling for delayed gratification (Richard H. Thaler and H. M. Shefrin 1981; Laibson 1997; Drew Fudenberg and David K. Levine 2006; Jess Benhabib and Alberto Bisin 2005; B. Douglas Bernheim and Antonio Rangel 2004; Faruk Gul and Wolfgang Pesendorfer 2001). We hoped to better understand both the behavioral and algorithmic roots of this phenomenon by conducting a series of behavioral and neurobiological experiments on intertemporal choice. The results of our behavioral experiments deviate significantly from the predictions of both normative and inner conflict models. The results of our neurobiological experiments provide new algorithmic insights into the mechanisms of intertemporal choice.

Disciplines
Psychology

Neuroeconomic Studies of Impulsivity: Now or Just as Soon as Possible?

By Paul William Glimcher, Joseph Kable, and Kenway Louie*

Existing behavioral studies of intertemporal choice suggest that both human and animal choosers are impulsive. One possible explanation for this is that they discount future gains in a hyperbolic or quasi-hyperbolic fashion (David I. Laibson 1997; Shane Frederick, George Loewenstein, and Ted O'Donoghue 2002). This observation stands in contrast to standard normative theory, which predicts exponential discounting for any single maximizing agent (Robert H. Strotz 1956). This disparity between empirical and normative approaches is typically explained by proposing that human choosers suffer from inner conflict, balancing an impulse for an immediate gratification against other forces calling for delayed gratification (Richard H. Thaler and H. M. Shefrin 1981; Laibson 1997; Drew Fudenberg and David K. Levine 2006; Jess Benhabib and Alberto Bisin 2005; B. Douglas Bernheim and Antonio Rangel 2004; Faruk Gul and Wolfgang Pesendorfer 2001). We hoped to better understand both the behavioral and algorithmic roots of this phenomenon by conducting a series of behavioral and neurobiological experiments on intertemporal choice. The results of our behavioral experiments deviate significantly from the predictions of both normative and inner conflict models. The results of our neurobiological experiments provide new algorithmic insights into the mechanisms of intertemporal choice.

* Glimcher: Center for Neuroeconomics, New York University, 4 Washington Place, 809, New York, NY 10003 (e-mail: glimcher@cns.nyu.edu); Kable: Center for Neuroeconomics, NYU, 4 Washington Place, 809, New York, NY 10003 (e-mail: kable@cns.nyu.edu); Louie: Center for Neuroeconomics, NYU, 4 Washington Place, 809, New York, NY 10003 (e-mail: klouie@cns.nyu.edu). The authors express gratitude to participants in the NYU Neuroeconomics seminar, with particular thanks to Andrew Caplin and Mark Dean.

I. Experiment One

We measured the preferences of 10 human subjects using a set of 576–720 binary choices that presented options differing in both delay and value. From these measurements, we estimated an indifference curve for each subject. This indifference curve, which can be modeled as the product of underlying utility and discount functions, was hyperbolic, as has been previously described (Leonard Green and Joel Meyerson 2004; Kris N. Kirby and Nino N. Marakovic 1995).

During a series of one-hour behavioral sessions, subjects were asked to make 144 intertemporal choices. Each round presented a choice between a certain immediate gain of $20 and a larger gain at a delay varying from 6 hours to 6 months (for example 1, 10, 21, 50, 90, and 180 days). Subjects were informed that the first session was unpaid. After completing three behavioral sessions (two of which were paid) and having used the debit cards described below to receive at least one delayed payment, the subjects completed one or two additional choice sessions, this time inside a brain scanner.

Across sessions, the exact values and delays presented in the choice set were varied by small amounts. At the conclusion of the second session (and each subsequent session), four choices were randomly selected from the set of choices made during that session, and the subjects were paid for those decisions. All payments were made through a commercial debit card system that allowed us to load the precise amount of the selected option at the precise time specified by the subject's choice. Subjects were reminded by e-mail at the time each payment was delivered into their debit accounts. The debit cards we employed are nationally accepted as credit cards at millions of locations throughout the United States. Subjects were thus free to consume their gains with negligible transaction costs. As a further benefit, the cards allowed us to monitor the actual consumption behavior of our subjects.

The behavioral data gathered in this way allowed us to identify, for each of the six delays we examined, the amount of money for which each subject was statistically indifferent, with $20 paid immediately. We then fit, to these six stochastic indifference points, both hyperbolic and exponential functions. These functions were equivalent to a representation of the discounted utilities that could be used to predict the stochastic pattern of choice made by each of our subjects. We found, as in previous studies, the behavior of our subjects was better described by hyperbolic rather than by exponential functions (Laibson 1997), implying that our subjects employed a hyperbolic-like discount function. We also found our subjects varied significantly in the rates of discounting implied by this measured function. Our most patient subject and our most impulsive subject differed by more than an order of magnitude in the hyperbolic constants that characterized their indifference curves.

These individually measured indifference curves permitted us, for each subject, to model the discounted utility of each delayed option presented to our subjects in the brain scanner. With this behavioral measurement in hand, we could then ask whether any activity in the brain of these subjects was correlated with the discounted utility of an option under consideration. We found that, in each of our subjects, the activity of the brain in three areas typically associated with option valuation (Allison N. McCoy et al. 2003; Howard C. Cromwell and Wolfram Schultz 2003; Hans C. Breiter et al. 2001; Nathaniel D. Daw et al. 2006; Samuel M. McClure, Michele K. York, and P. Read Montague 2004; John P. O'Doherty 2004) showed a clear correlation with this behaviorally derived function. Put another way, brain activity measured in the medial prefrontal cortex, the ventral striatum, and the posterior cingulate cortex had many of the properties of that subject's discounted utility function. Perhaps surprisingly, we saw no evidence in any of these areas of neural functions that were better correlated with functions that were either steeper or shallower (in exponential *or* hyperbolic terms) than the behaviorally measured discounted utility function for that subject. More unambiguously, we also saw no evidence that activity in any of these areas showed different discount rates. We saw no evidence of separable neural agents that could account for the multiple selves that are used to explain hyperbolic-like discounting behavior. This finding argues strongly against the hypothesis that multiple selves, with different discount functions, are instantiated as discrete neural systems *at the proximal algorithmic level.*

This finding contradicts an earlier report (McClure et al. 2004) which appeared to support the dual-self β–δ model of Laibson (1997), at a neurobiological level. In that report, subjects were asked to make ~40 choices between gains available at three delays. Although that study did not examine the choices made by subjects, the authors reported that they observed higher brain activity for immediate option sets in these same three areas. From this enhanced neural response for immediate options, the authors concluded that these brain areas were an "impetuous" agent of the type that would be predicted for the β component of the β–δ model. We note, however, that an area where activity was linearly correlated with a hyperbolic-like discounted utility function of any kind (which necessarily favors immediate over delayed gains) would also show this property. The critical test of the multiple-selves model at a neural level, which these authors did not perform, would be to show that the area in question discounted faster than behavioral measurements of the subjects' indifference curves or, at least, that different brain areas discounted at different rates. We show that this is not the case.

Our subjects showed hyperbolic-like indifference curves that could be characterized as discounted utility functions. The areas of their brains known to participate in option valuation showed surprisingly similar functions. Although the hyperbolic or exponential coefficients that described the steepness of these neural and behavioral functions varied widely from subject to subject, the behaviorally and neurally measured functions made on a single subject appeared to be tightly, and surprisingly linearly, correlated.

II. Experiment Two

Why do choosers discount hyperbolically? The standard explanation is that this is the result of inner conflict between forces favoring impatience and those favoring patience. Our neurobiological measurements, however, showed no evidence that these forces reside as physical processes within the human brain. This significant discontinuity between the behavioral models and the neural structures that actually produce behavior led us to reexamine the behavioral phenomenon of hyperbolic discounting. If internal divisions do not account for intertemporal choice behavior, then perhaps intertemporal preferences are more complicated than previously has been supposed. In a second experiment, we set out to test the hypothesis that the discounted utilities of all prizes, in all choice sets, can be described as functions of the interval between the immediate present and the time of option delivery, as is widely assumed.

We repeated experiment one with a new group of subjects, but this time randomly intermixed two sets of choices. The first set of choices was identical to that employed in experiment one (the immediate-option set), while the second set used either the same values as choice set one or a set of higher values, with an additional 60-day front-end delay added to all options (the delayed-option set). Thus, the earliest possible option, which appeared in all of the choices in the second set, was a gain of \$20 at a delay of 60 days, or a gain of \$30–\$60 at a delay of 60 days. The delivery date for the more delayed option in these choices ranged from 61 days to 180 days.

We then analyzed the data from each choice set separately, as described in experiment one. Choice data from the immediate-option set was again used to identify the point of stochastic indifference for each of six delays. Hyperbolic and exponential functions were fit to these indifference points, and the functions we obtained were not statistically distinguishable from those observed in experiment one. The exact same analysis was then performed on the delayed-option set. For this analysis of the delayed-option set, we plotted the stochastic indifference points as a function of the interval between the two options in the choice set. On this graph, \$20 at a delay of two months would constitute the earliest possible time point and, as in the immediate-option set, this option was assigned a discounted utility of one. Perhaps surprisingly, we found that for each individual subject the hyperbolic function that stochastically fit the choice data from the immediate-option set also fit the choice data from the delayed-option set. The indifference curves of our subjects were just as hyperbolic when making choices at delays of two months as they were when making choices at no delay. This is a behavioral observation not predicted by existing multiple-selves models.

The preference data we gathered in this experiment were thus similar to the preference data we gathered in experiment one, but we place some additional constraints on preference ordering. Specifically, the indifference curves were found to be functions not only of gain and delay but also of the time of the earliest possible gain in the choice set. In other words, our subjects were not simply impulsive, strongly preferring immediate gains. Instead, they appeared to strongly prefer gains "as soon as possible" regardless of whether "as soon as possible" was a matter of minutes or months.

While this new observation may be useful, we can make an additional measurement with the brain scanner. We know that brain activity in the ventral striatum, the posterior cingulate cortex, and the anterior cingulate cortex shows a correlation (in fact a surprisingly linear correlation) with discounted utility measured in the immediate-option choice set. We can ask whether activity in these areas is also correlated with discounted utility as measured in the delayed-option choice set, and we can ask how activity during these two choice sets is related.

We therefore examined the brain activity of our subjects while they made these immediate and delayed choices. Recall that the brain scanning data from experiment one revealed neural activation functions that were approximately linearly correlated (at the within-subject level), with the discounted utilities of the delayed rewards presented as options in that experiment. With these data we can predict the discounted utility of a delayed choice from that choice set using a neural measurement.

First, the brain scanning data indicate that the discounted utilities measured in the delayed-option choice set are correlated approximately with brain activation in all of these areas. Second, the data show that overall activity for the delayed-option choice set is much lower than it is for the equally valued immediate-option choice set. Empirically, we observed that the overall decrease in activity, the fractional rescaling of the neural activation function, roughly can be predicted by an exponential fit to the other neural activation function gathered during choices made about the immediate-option set. The decline in activity observed for a two-month delayed option in the immediate set reflects a scaling factor that predicts, roughly, activity to the two-month delayed option in the delayed-option choice set. This may be an important mechanistic observation. Despite the fact that our subjects prefer gains "as soon as possible" regardless of when "as soon as possible" is, their striatal and cingulate brain activity is a decreasing monotonic function of the delay to the soonest possible reward. The following section briefly presents a model of neurobiological computations that may be relevant to both the behavioral and neural data presented here.

III. Model

Next, we present a two-stage stochastic model of neural activation that predicts muscle contraction. In the first stage of the model, for each option, striatal activity (at a distinct anatomical location for each option) is a monotonic increasing function of value. For immediately available options, this is now a well-documented property of the striatum. The data presented here suggest that these activity levels are also a decreasing monotonic function of delay from the *present* to the time the option is realized. We write this neural activation function as Activation $=\delta_1(t)U_1(v)$.

Our preexisting evidence suggests that these activations related to value are passed (indirectly) to the parietal cortex. Within the parietal cortex it is also known that, for available actions, the activity of computational elements (at distinct anatomical locations for each option) is a monotonic increasing function of the *relative* value of the striatal activity, in this case $\delta_1(t)U_1(v)$. The form of this rescaling operation has now been well described in other cortical areas and is believed to take the form of $[\delta_1(t,\tau)U_1(v)]$ divided by $\Sigma\omega_{i,j}[\delta_1(t,\tau)U_1(v)] + C_0$, where $\delta_1(t,\tau)$ is the exponential decrease in activity (for option 1) as a function of the delay to reward and the *neuronal* discount rate; $U_1(v)$ is the increasing monotone relationship between the value of option 1 and activity; $\omega_{i,i}$ is a weighting term that maximizes statistical independence in the activity of the computational elements (after Odelia Schwartz and Eero P. Simoncelli 2001); and C_0 is a constant. This rescaling operation is then used as the independent variable in a logit function that yields the probability that the muscles responsible for selecting option 1 are activated. For a binary choice in our task this would resolve to:

parietal activity =

$$\frac{[\delta_1(t,\tau)U_1(v)]}{\omega_{1,j}[\delta_i(t,\tau)U_i(v)]+\omega_{2,j}[\delta_2(t,\tau)U_2(v)]+C_0}.$$

While the choice-theoretic implications of this identified neural algorithm are unclear, it is clear that these computations are being performed by neural circuits without which choice does not occur. One striking feature of these computations for economists may be the observation that the activity of all computational elements is always influenced by the size and delivery time of the soonest possible reward, a reward that might be considered a temptation in a choice-theoretic setting.

IV. Discussion

We employed both behavioral and neurobiological methods to examine intertemporal choice. Our goal was to use a revealed preference approach to study choice and then to use the results of this revealed preference analysis as the starting point for a neurobiological analysis. While we did find behavioral evidence for hyperbolic or quasi-hyperbolic discounting, we found that our neurobiological data did not support the hypothesis that these discount functions are the product of multiple agents within the human brain.

It has been argued recently (Gul and Pesendorfer, 2006) that a choice-based theory cannot be falsified by the observation that the algorithmic structure of the human brain is incompatible with the computations required by that theory. This is undoubtedly true. Still, at a purely strategic level it seems imprudent to ignore any observable that may provide insight into choice behavior. On these grounds we undertook a second experiment with two goals. First, we hoped to characterize more completely choice behavior under conditions of variable delay. The existing behavioral models (which we found incompatible with our neural measurements) make clear predictions about choices among multiple delayed alternatives we hoped to test. Second, we wanted to examine further the neural evidence for models of internal conflict. The simplest neurobiological test for an "impetuous region" is to scan subjects making choices from sets that either do or do not include an immediate option (a point made to us by Loewenstein). An impetuous region should be active only in the immediate-option set—a distinction that should make the impetuous region easy to identify neurally.

At the behavioral level, we found that rather than being simply impulsive, as has been previously supposed, our choosers seemed to adopt an "as soon as possible" rule. The soonest possible gains were preferred at a more than exponential rate, regardless of when those soonest possible gains became available, and our neurobiological data again showed no evidence for an impetuous self. Finally, the relationship between a neural variable (activity in the ventral striatum, anterior cingulate, and posterior cingulate) and discounted utility, as measured in both choice sets, may impose some additional constraints on the representations of utility that future models can employ. Finally, the model we developed from our neurobiological observations can predict brain activity and muscle activations, and may raise interesting questions for economic study at the axiomatic level.

V. Summary

A small group of scholars committed to the revealed preference approach have recently begun to propose that economics must search for additional observables that can be used to test and examine existing models. Andrew Caplin and Mark Dean (2007), for example, have proposed that the axiomatic reasoning that has characterized the study of revealed preference can be extended to the study of neurobiological variables that actually govern choice behavior. This seems to us an incredibly powerful new direction that could revolutionize both economics and neuroscience. Neurobiologists interested in the algorithmic structure of the brain have begun to reveal many of the proximal mechanisms by which choice is produced. Algorithmic mechanisms for preference ordering, stochastic choice, and even value construction have all been identified in recent years. Given these new observations, it seems only natural to ask whether these already existing observables can be used to examine, even falsify, existing revealed preference-based theories of choice. At the moment, neuroeconomists seem to be dividing into two camps. The first of these camps has used neurobiological data to argue against a revealed preference analyses of choice (Colin Camerer, Loewenstein, and Drazen Prelec 2005). Here, we argue for a different road. We believe that the revealed preference approach brings an unparalleled power to the study of choice. Contemporary neurobiology brings a similar power to the study of mechanism. It is the combination of these two tried and tested approaches that we believe can revolutionize both disciplines.

REFERENCES

Benhabib, Jess, and Alberto Bisin. 2005. "Modeling Internal Commitment Mechanisms and Self-Control: A Neuroeconomics Approach to Consumption-Saving Decisions." *Games and Economic Behavior*, 52(2): 460–92.

Bernheim, B. Douglas, and Antonio Rangel. 2004. "Addiction and Cue-Triggered Decision Processes." *American Economic Review*, 94(5): 1558–90.

Breiter, Hans C., Itzhak Aharon, Daniel Kahneman, Anders Dale, and Peter Shizgal. 2001. "Functional Imaging of Neural Responses to Expectancy and Experience of Monetary Gains and Losses." *Neuron*, 30(2): 619–39.

Camerer, Colin, George Loewenstein, and Drazen Prelec. 2005. "Neuroeconomics: How Neuroscience Can Inform Economics." *Journal of Economic Literature*, 43(1): 9–64.

Caplin, Andrew, and Mark Dean. 2007. "The Neuroeconomic Theory of Learning." *American Economic Review (Papers and Proceedings).* 97(2): 148–52.

Cromwell, Howard C., and Wolfram Schultz. 2003. "Effects of Expectations for Different

Reward Magnitudes on Neuronal Activity in Primate Striatum." *Journal of Neurophysiology*, 89(5): 2823–38.

Daw, Nathaniel D., John P. O'Doherty, Peter Dayan, Ben Seymour, and Raymond J. Dolan. 2006. "Cortical Substrates for Exploratory Decisions in Humans." *Nature*, 441(7095): 876–79.

Frederick, Shane, George Loewenstein, and Ted O'Donoghue. 2002. "Time Discounting and Time Preference: A Critical Review." *Journal of Economic Literature*, 40(2): 351–401.

Fudenberg, Drew, and David K. Levine. 2006. "A Dual Self Model of Impulse Control." *American Economic Review*, 96(5): 1449–76.

Green, Leonard, and Joel Myerson. 2004. "A Discounting Framework for Choice with Delayed and Probabilistic Rewards." *Psychological Bulletin*, 130(5): 769–92

Gul, Faruk, and Wolfgang Pesendorfer. 2001. "Temptation and Self-Control." *Econometrica*, 69(6): 1403–35.

Gul, Faruk, and Wolfgang Pesendorfer. 2006. "The Case for Mindless Economics." Unpublished.

Kirby, Kris N., and Nino N. Marakovic. 1995. "Modeling Myopic Decisions: Evidence for Hyperbolic Delay Discounting with Subjects and Amounts." *Organizational Behavior and Human Decision Processes*, 64(1): 22–30.

Laibson, David I. 1997. "Golden Eggs and Hyperbolic Discounting." *Quarterly Journal of Economics*, 112(2): 443–77.

McClure, Samuel M., David I. Laibson, George Loewenstein, and Jonathan D. Cohen. 2004. "Separate Neural Systems Value Immediate and Delayed Monetary Rewards." *Science*, 306(5695): 503–07.

McClure, Samuel M., Michele K. York, and P. Read Montague. 2004. "The Neural Substrates of Reward Processing in Humans: The Modern Role of Functional Magnetic Resonance Imaging." *The Neuroscientist*, 10(3): 260–68.

McCoy, Allison N., Justin C. Crowley, Golnaz Haghighian, Heather L. Dean, and Michael L. Platt. 2003. "Saccade Reward Signals in Posterior Cingulate Cortex." *Neuron*, 40(5): 1031–40.

O'Doherty, John P. 2004. "Reward Representations and Reward-Related Learning in the Human Brain: Insights from Human Neuroimaging." *Current Opinion in Neurobiology*, 14(6): 769–76.

Strotz, Robert H. 1956. "Myopia and Inconsistency in Dynamic Utility Maximization." *Review of Economic Studies*, 23(3): 165–80.

Thaler, Richard H., and H. M. Shefrin. 1981. "An Economic Theory of Self-Control." *Journal of Political Economy*, 89(2): 392–406.

This article has been cited by:

1. Daniel Read, Christopher Y. Olivola, David J. Hardisty. 2017. The Value of Nothing: Asymmetric Attention to Opportunity Costs Drives Intertemporal Decision Making. *Management Science* **63**:12, 4277-4297. [Crossref]
2. Daniel Read, Marc Scholten. Future-Oriented Decisions: Intertemporal Choice 35-50. [Crossref]
3. George Ainslie. 2017. Intertemporal Bargaining in Habit. *Neuroethics* **10**:1, 143-153. [Crossref]
4. David L. Barack, Michael L. Platt. Engaging and Exploring: Cortical Circuits for Adaptive Foraging Decisions 163-199. [Crossref]
5. Marco Stimolo. 2016. An economic agent in my brain? A critical analysis of multiple-self models in neuroeconomics. *Review of Social Economy* **74**:4, 329-348. [Crossref]
6. Shinsuke Ikeda. Hyperbolic Discounting and Self-Destructive Behaviors 43-65. [Crossref]
7. Diana Moreira, Marta Pinto, Fernando Almeida, Susana Barros, Fernando Barbosa. 2016. Neurobiological bases of intertemporal choices: A comprehensive review. *Aggression and Violent Behavior* **26**, 1-8. [Crossref]
8. Oleg Urminsky, Gal Zauberman. The Psychology of Intertemporal Preferences 141-181. [Crossref]
9. Tsuyoshi Setogawa, Takashi Mizuhiki, Narihisa Matsumoto, Fumika Akizawa, Munetaka Shidara. 2014. Self-choice enhances value in reward-seeking in primates. *Neuroscience Research* **80**, 45-54. [Crossref]
10. Tommy C. Blanchard, Lauren S. Wolfe, Ivo Vlaev, Joel S. Winston, Benjamin Y. Hayden. 2014. Biases in preferences for sequences of outcomes in monkeys. *Cognition* **130**:3, 289-299. [Crossref]
11. Eric J. Johnson, Roger Ratcliff. Computational and Process Models of Decision Making in Psychology and Behavioral Economics 35-47. [Crossref]
12. Joseph W. Kable. Valuation, Intertemporal Choice, and Self-Control 173-192. [Crossref]
13. Jim Parkinson, Patrick Haggard. 2013. Hedonic value of intentional action provides reinforcement for voluntary generation but not voluntary inhibition of action. *Consciousness and Cognition* **22**:4, 1253-1261. [Crossref]
14. Christopher J. Ruhm. 2012. Understanding overeating and obesity. *Journal of Health Economics* **31**:6, 781-796. [Crossref]
15. Jin-Zhen Li, Dan-Yang Gui, Chun-Liang Feng, Wen-Zhong Wang, Bo-Qi Du, Tian Gan, Yue-Jia Luo. 2012. Victims' Time Discounting 2.5 Years after the Wenchuan Earthquake: An ERP Study. *PLoS ONE* **7**:7, e40316. [Crossref]
16. Don Ross. The Economic Agent 691-735. [Crossref]
17. Don Ross. 2011. Estranged parents and a schizophrenic child: choice in economics, psychology and neuroeconomics. *Journal of Economic Methodology* **18**:3, 217-231. [Crossref]
18. Jack Vromen. 2011. Neuroeconomics: two camps gradually converging: what can economics gain from it?. *International Review of Economics* . [Crossref]
19. John Cawley, Christopher J. Ruhm. The Economics of Risky Health Behaviors11We thank the editors of this Handbook, Pedro Pita Barros, Tom McGuire, and Mark Pauly, for their feedback and helpful guidance. We also thank the other authors in this volume for their valuable feedback and comments at the Authors' Conference, and we are grateful to Abigail Friedman for transcribing the comments at that conference 95-199. [Crossref]
20. Hiroyuki Nakahara, Sivaramakrishnan Kaveri. 2010. Internal-Time Temporal Difference Model for Neural Value-Based Decision Making. *Neural Computation* **22**:12, 3062-3106. [Crossref]

21. Gharad Bryan, Dean Karlan, Scott Nelson. 2010. Commitment Devices. *Annual Review of Economics* **2**:1, 671-698. [Crossref]

22. Scott Rick. 2010. Losses, gains, and brains: Neuroeconomics can help to answer open questions about loss aversion. *Journal of Consumer Psychology* . [Crossref]

23. Glenn Harrison, Don Ross. 2010. The methodologies of neuroeconomics. *Journal of Economic Methodology* **17**:2, 185-196. [Crossref]

24. Jack Vromen. 2010. On the surprising finding that expected utility is literally computed in the brain. *Journal of Economic Methodology* **17**:1, 17-36. [Crossref]

25. Lee Anne Fennell. 2009. Willpower and Legal Policy. *Annual Review of Law and Social Science* **5**:1, 91-113. [Crossref]

26. Constant D. Beugré. 2009. Exploring the neural basis of fairness: A model of neuro-organizational justice. *Organizational Behavior and Human Decision Processes* **110**:2, 129-139. [Crossref]

27. Tobias Kalenscher. Decision-making and Neuroeconomics . [Crossref]

28. Julia Trommershäuser, Laurence T. Maloney, Michael S. Landy. The Expected Utility of Movement 95-111. [Crossref]

29. Paul W. Glimcher. Choice 503-521. [Crossref]

30. Elke U. Weber, Eric J. Johnson. 2009. Mindful Judgment and Decision Making. *Annual Review of Psychology* **60**:1, 53-85. [Crossref]

31. P.H. Kenning, H. Plassmann. 2008. How Neuroscience Can Inform Consumer Research. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **16**:6, 532-538. [Crossref]

32. Don Ross. 2008. TWO STYLES OF NEUROECONOMICS. *Economics and Philosophy* **24**:03, 473. [Crossref]

33. Isabelle Brocas, Juan D Carrillo. 2008. The Brain as a Hierarchical Organization. *American Economic Review* **98**:4, 1312-1346. [Crossref]

34. Andrew Caplin,, Mark Dean. 2008. Economic Insights from "Neuroeconomic" Data. *American Economic Review* **98**:2, 169-174. [Citation] [View PDF article] [PDF with links]

35. George Loewenstein, Scott Rick, Jonathan D. Cohen. 2008. Neuroeconomics. *Annual Review of Psychology* **59**:1, 647-672. [Crossref]

36. T KALENSCHER, C PENNARTZ. 2007. Is a bird in the hand worth two in the future? The neuroeconomics of intertemporal decision making. *Progress in Neurobiology* . [Crossref]

37. Gregory S. Berns, David Laibson, George Loewenstein. 2007. Intertemporal choice – toward an integrative framework. *Trends in Cognitive Sciences* **11**:11, 482-488. [Crossref]